IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re Application of:

Jeff EDER

Serial No.: 09/761,671

Filed: January 18, 2001

For: A DETAILED METHOD OF AND SYSTEM FOR MODELING AND ANALYZING BUSINESS IMPROVEMENT PROGRAMS

Group Art Unit: 3624

Examiner: Y. Retta

Brief on Appeal

Honorable Commissioner of Patents and Trademarks
Washington, D.C. 20321

Sir:

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Real party in interest

Asset Reliance, Inc. (dba Asset Trust, Inc.)

Related appeals

An appeal for U.S. Patent Application 09/688,983 filed October 17, 2000 may be affected by or have a bearing on this appeal. An appeal for U.S. Patent Application 10/012,374 filed December 12, 2001 may be affected by or have a bearing on this appeal. An appeal for U.S. Patent Application 10/329,172 filed December 23, 2002 may be affected by or have a bearing on this appeal.

Status of Claims

Claims 69 - 96 are rejected and are the subject of this appeal. No other claims are pending. Claims 1 - 68 and 97 - 103 have previously been cancelled without prejudice. Claims 104 - 118 were withdrawn due to a restriction requirement.

Status of Amendments

An Amendment/Reply After Final Rejection was submitted on July 7, 2006.

Summary of Claimed Subject Matter

One embodiment of a detailed method of and system for modeling and analyzing business improvement programs according to the present invention is best depicted in Figures 1 – 15 of the specification for the instant application. Figure 1 gives an overview of the major processing steps which include aggregating, converting and integrating data from a plurality of database management systems for use in analysis, analyzing the data as required to: optionally value growth options, identify value drivers by element of value, develop predictive models for each component of value, value the elements of value, analyze improvement programs and produce reports.

One embodiment of the system for modeling and analyzing business improvement programs is exemplified in independent claim 69 where a modeling method integrates data from a plurality of management systems for use in analysis, analyzes the data using a series of models to identify value drivers by element of value and create a contribution summary for each element of value before using the contribution summary to create a plurality of network models for aspects of financial performance. More specifically, data from the database management systems associated with a plurality of enterprise transaction systems are integrated in accordance with a common data dictionary as described in FIG. 5A - B and paragraphs 78 - 106. The integrated data are then analyzed using a series of models in order to identify value drivers by element of value and develop an element impact summary in accordance with the procedure detailed in FIG. 7A – E and paragraphs 115 – 164. The element impact summaries are then used as inputs in order to develop optimized predictive models of aspects of current operation financial performance as described in FIG. 9A – C and paragraphs 171 – 177.

A second embodiment of the system for modeling and analyzing business improvement programs is exemplified in independent claim 77 where a program storage device implements a modeling method that integrates and converts data from a plurality of management systems for use in analysis, analyzes the data using a series of time series models to identify value drivers by element of value and create a contribution summary for each element of value. The element of value contribution summaries are used to create a plurality of network models that are used to analyze and simulate aspects of current operation financial performance. More specifically, data from the database management systems associated with a plurality of enterprise transaction systems are integrated in accordance with a common data dictionary as described in FIG. 5A - B and paragraphs 78 - 106. The integrated data are then analyzed with a series of models in order to develop an element impact summary for each element of value in accordance with the procedure detailed in FIG. 7A – E and paragraphs 115 – 164. The element impact summaries are then used as inputs in order to develop optimized predictive models of aspects of current operation financial performance as described in FIG. 9A – C and paragraphs 171 – 177. The

models developed in this process can be used for forecasting. The network models are also used to identify a current operation value contribution for each of the elements of value as described in FIG. 12 and paragraphs 178 - 188. The performance of the network models are then simulated as required to allow the user to identify the impact of operational changes on financial performance and/or to identify how to optimize one or more aspects of current operation financial performance as described in paragraphs 171 -177, 211 – 216, FIG. 9A – C and FIG. 15.

A third embodiment of the system for modeling and analyzing business improvement programs is exemplified in independent claim 85 where an apparatus integrates and converts data from a plurality of enterprise transaction systems for use in analysis, analyzes the data using a series of time series models to identify value drivers by element of value and create a contribution summary for each element of value. The element of value contribution summaries are used to create a plurality of network models that are then used to analyze aspects of current operation financial performance in order to identify a set of changes that will optimize aspects of financial performance. More specifically, data from the database management systems associated with a plurality of enterprise transaction systems are integrated in accordance with a common data dictionary as described in FIG. 5A - B and paragraphs 78 - 106. The integrated data are then analyzed with a series of models in order to develop an element impact summary for each element of value in accordance with the procedure detailed in FIG. 7A – E and paragraphs 115 – 164. The element of value impact summaries are then used as inputs in order to develop optimized predictive models of aspects of current operation financial performance as described in FIG. 9A – C and paragraphs 171 – 177. The performance of the network models are then simulated as required to allow the user to identify how to optimize one or more aspects of current operation financial performance as described in paragraphs 171 - 177, 211 – 216, FIG. 9A – C and FIG. 15.

A fourth embodiment of the system for modeling and analyzing business improvement programs is exemplified in independent claim 92 where a method integrates and converts data from a plurality of enterprise transaction systems for use in analysis, analyzes the data using a series of time series models to identify value drivers by element of value and create a contribution summary for each element of value. The element of value contribution summaries are used to create a plurality of network models that are used to analyze and simulate aspects of current operation financial performance that are used for identifying changes to optimize aspects of financial performance. More specifically, data from the database management systems associated with a plurality of enterprise transaction systems are integrated in accordance with a common data dictionary as described in FIG. 5A - B and paragraphs 78 - 106. The integrated data are then analyzed with a series of models in order to develop an element impact summary for each element of value in accordance with the procedure detailed in FIG. 7A – E and paragraphs 115 – 164. The element impact summaries are then

used as inputs in order to develop optimized predictive models of aspects of current operation financial performance as described in FIG. 9A – C and paragraphs 171 – 177. The performance of the network models are then simulated as required to allow the user to identify how to optimize one or more aspects of current operation financial performance as described in paragraphs 171 - 177, 211 – 216, FIG. 9A – C and FIG. 15.

Issues

Issue 1 - Whether claims 69 - 76 are patentable under 35 USC 103 over Bielinski, Daniel W.; "How to sort out the premium drivers of post-deal value"; Mergers and Acquisitions; Jul/Aug 1993, Vol. 28, Iss.1; pg. 33, 5 pgs (hereinafter Bielinski), further in view of Brown, Carol E, Coakley, James, Phillips, Mary Ellen; 'Neural Networks Enter the World of Management Accounting""; Management Accounting; Montvale, NJ; May 1995, 5 pages (hereinafter Brown)?

Issue 2 - Whether claims 77 - 84 are patentable under 35 USC 103 over Bielinski in view of Brown?

Issue 3 - Whether claims 85 - 91 are patentable under 35 USC 103 over Bielinski in view of Brown?

Issue 4 - Whether claims 92 - 96 are patentable under 35 USC 103 over Bielinski in view of Brown?

The Argument

Grouping of Claims

For each ground of rejection which Appellant contests herein which applies to more than one claim, such additional claims, to the extent separately identified and argued below, do not stand and fall together.

Issue 1 - Whether claims 69 - 76 are patentable under 35 USC 103 over Bielinski in view of Brown?

The claims are patentable because the cited combination of documents used to support the rejection of claims 69 – 76 fails to establish a prima facie case of obviousness. The cited combination fails to establish a prima facie case of obviousness because:

1. the cited documents teach away from the proposed combination;
2. the cited combination requires a change in the principles governing the operation of the methods disclosed by Bielinski,
3. the cited combination destroys the ability of at least one of the cited methods to function; and
4. the cited combination fails to meet any of the criteria for establishing a prima facie case of obviousness.

The first reason the cited combination of documents fails to establish the prima facie case of obviousness required to sustain the rejections of claim 69 - 76 is that the cited combination of documents teaches away from the proposed combination. MPEP § 2145 X.D.2 provides that: "it is improper to combine references where the references teach away from their combination." Both documents, Bielinski and Brown describe methods for analyzing changes in the market value of a firm. Brown describes the use of a neural network by Deere to analyze changes in stock price (stock price = market value divided by the number of shares). Bielinski describes Value Based Management (hereinafter, VBM) a method that relies on the principles of Shareholder Value Analysis (hereinafter, SVA) developed by Rappaport (Bielinski, page 3) to identify specific actions that can be taken to improve value. The two documents teach diametrically opposed methods for analyzing and completing the same tasks. In doing this, they teach away from the proposed combination in at least five ways as detailed below.

1. Incompatible market value determinants. Bielinski teaches one of the principles of SVA, namely that there are three determinants of market value: cash flow, long term cash flow forecasts and the riskiness of the cash flow (See Evidence Appendix, Rappaport, page 70). Brown teaches that there are 40 indicators that determine market value (See Evidence Appendix, Brown, page 4). It clearly would be improper to combine a method that relies on the principle that there are only three determinants of market value with a method that teaches that there are 40 determinants of market value.

2. Incompatible market models. Bielinski also implicitly teaches another of the principles of SVA, namely that there is an efficient market. The efficient market theory teaches that enterprise value is determined by cash flow and the riskiness of the cash flow. It also teaches that the riskiness of the cash flow can be determined by the use of a beta measure as taught by Rappaport (See Evidence Appendix, Rappaport, page 39). Brown teaches and relies on the inefficient market theory as one of the principle goals of the neural network system it describes is to achieve returns above the S&P 500 (See Evidence Appendix, Brown, page 4). It is well known by those of average skill in the art that the efficient market theory teaches, among other things, that it is not possible to systematically achieve returns above S&P 500. It clearly would be improper to combine the teachings of a document that relies on the efficient market theory with the teachings of a document that teaches a method designed to identify and exploit an inefficient market.

3. Incompatible time frames. Bielinski teaches and relies on the long term analysis of historical cash flow: "five years of historical cash flow are added up to arrive at a cumulative baseline cash flow number" (See Evidence Appendix, Bielinski, page 2). Brown teaches forecasting short term changes in performance (i.e. "modeling expected future returns") which produces an 80% monthly turnover in the portfolio (See Evidence Appendix, Brown, page 4). It clearly would be improper to combine the teachings of a document that discloses a method for completing 5 year analyses of historical performance with a method that teaches the prediction of short term changes in market value based on daily and weekly changes in a variety of factors. This is particularly true since Bielinski specifically teaches away from the use of projections for any aspect of analysis (See Evidence Appendix, Bielinski, page 1).

4. Incompatible model topology. Bielinski teaches another of the principles of SVA, namely the use of a tree topology to analyze changes in the value of a commercial enterprise (See Evidence Appendix, Rappaport, page 172). Brown teaches reliance on a network topology to complete the same analyses (See Evidence Appendix, Brown, page 4). It clearly would be improper to combine the teachings of a document that discloses the use of a tree to analyze market value changes with a method that teaches the use of a network topology for analyzing the same thing.

5. Incompatible analysis methodology. Bielinski teaches the use of sensitivity analysis in evaluating changes in the value of a commercial enterprise (See Evidence Appendix, Bielinski, pages 1, 2, 3 and 4). Brown teaches reliance on the neural network scoring capability to rank expected future returns for each stock in the portfolio (See Evidence Appendix, Brown, page 4). Because returns equal changes in value plus dividends (which tend to be fixed in value), the different analyses are analyzing the same thing. It clearly would be improper to combine the teachings of a document that discloses the use sensitivity analysis with a method that teaches the use scoring for analyzing the same thing.

The second reason that the cited combination of documents fails to establish a prima facie case of obviousness for claims 69 - 76 is that the proposed combination of documents would change the principle of operation of the Bielinski method. MPEP 2143.01 provides that when "the proposed modification or combination of the prior art would change the principle of operation of the prior art invention being modified, then the teachings of the references are not sufficient to render the claims prima facie obvious. In re Ratti, 270 F.2d 810, 123 USPQ 349 (CCPA 1959)". Bielinski clearly states that the VBM method relies on the principles of the SVA method of Rappaport (See Evidence Appendix, Bielinski, page 3). As mentioned previously, some of the SVA principles are: tree based analysis of value, revenue, etc. and reliance on the efficient market hypothesis which teaches that cash flow fully explains the value of an enterprise. The cited combination would change these principles by:

1. utilizing a network analysis in place of a tree based analysis for at least some portion of the model,
2. acknowledging that the efficient market theory does not explain all value changes, and
3. making the related acknowledgement that cash flow explains <u>only a portion</u> of the value of an enterprise (the current operation portion).

The cited combination would also change another principle of operation for the VBM method, namely the strict reliance on historical cash flow and the related prohibition against using projections of any kind (See Evidence Appendix, Bielinski, page 2). It is well known by those of average skill in the art that an optimization analysis requires a forward looking model for use in evaluating the tradeoffs among different future alternatives. The Examiner has proposed using the VBM method to support optimization analyses. A modification to support that type of analysis would require changing the backward looking VBM methodology to a forward looking methodology. Given the four changes in principle of operation required to support the proposed combination, the teachings of the cited combination are not sufficient to render the claims prima facie obvious.

The third reason the cited combination of documents fails to establish a prima facie case of obviousness for claims 69 - 76 is that it the proposed combination of Bielinski and Brown would destroy the ability of the methods described by these documents to function. It is well established that when a modification of a reference destroys the intent, purpose or function of an invention such a proposed modification is not proper and the prima facie cause of obviousness cannot be properly made (In re Gordon 733 F.2d 900, 221 U.S.PQ 1125 Fed Circuit 1984). The operation of the VBM methodology requires that the inputs to each node in the tree arithmetically combine to produce a number that is then passed on to higher levels in the tree (See Evidence Appendix, Rappaport, page 172). It is well known to those of average skill in the art that the use of a neural network in place of any part of the tree would destroy the ability to arithmetically generate the numbers required at each tree node. In short the proposed, theoretical combination would destroy the ability of the VBM method taught by

Bielinski to function. In a similar manner, imposing a tree topology on the methods of Brown would destroy the ability of the value analysis method taught by Brown to function. This in turn provides additional evidence that the proposed combination is improper and that the Examiner has failed to establish the prima facie case of obviousness required to sustain the rejection of a single claim.

The fourth reason the cited combination of documents fails to establish the prima facie case of obviousness is that it fails to meet the criteria required for establishing a prima facie case of obviousness. MPEP 2142 provides that: "in order to establish a prima facie case of obviousness, three basic criteria must be met. First, there must be some suggestion or motivation to modify the reference or to combine reference teachings. Second, there must be a reasonable expectation of success. Finally, the prior art reference (or references when combined) must teach or suggest all the claim limitations." As detailed below, the cited combination fails to meet all three criteria for establishing a prima facie case of obviousness required to sustain the rejection of claims 69 – 76:

1) The cited combination fails to meet the first criteria for establishing a prima facie case of obviousness for claims 69 - 76 because it does not provide any evidence indicating that there was any suggestion, teaching or motivation in the prior art to modify or combine the teachings of Bielinski and/or Brown. In particular, the Examiner has not identified how the combination of teachings would improve the functionality of either method and has previously provided documents that indicated there was a motivation not to make the cited combination. The Examiner has mentioned the identification of value drivers as a possible motivation. However, this unpersuasive as Rappaport already identifies the seven financial value drivers (See Evidence Appendix, Rappaport, page 171) so there is no need to use a neural net (or anything else) to identify them. This indicates that the Examiner has used hindsight to justify a combination that anyone relying solely on the cited documents would never propose.

2) The cited combination also fails to meet the second criteria for establish a prima facie case of obviousness for claims 69 - 76 because it does not cite a combination of teachings that has a reasonable expectation of success. Reasons the cited combination of documents would be expected to fail include: the cited combination teaches incompatible methods and time frames for market valuation and optimization analysis requires a forward looking model rather than the backward looking model like VBM.

3) The cited combination fails to meet the third criteria because it does not teach or suggest one or more of the claim limitations for each of the claims. For example, the cited combination does not identify a method for optimizing any aspect of performance, any method for developing models of element of value impact, any method for

integrating data and/or any method for creating time series network models. The Examiner did supplement the information provided by Bielinski and Brown with “official notice” that optimization is old and well known. However, this official notice is moot because, as detailed above, the Examiner has not identified a forward looking model capable of supporting an optimization analysis.

As stated above, there at least four reasons why the cited combination of documents fails to establish a prima facie case of obviousness. There is also a fifth reason that claims 69 - 76 are patentable. The fifth reason is that the claimed invention produces results that are concrete, tangible and useful. In view of the previously documented shortcomings in the cited combination of documents that were used as the basis of the claim rejection, it also clear that the claims represent an invention that is novel, surprising, new and non-obvious. Furthermore, the claimed invention produces results that help satisfy a long felt need for improved capabilities for understanding the linkage between operational decisions and market value.

Issue 2 - Whether claims 77 - 84 are patentable under 35 USC 103 over Bielinski in view of Brown?

The claims are patentable in view of the shortcomings in the cited combination of documents and the associated arguments that support their use that were detailed in issue 1. In particular, claims 77 - 84 are allowable for the first, second, third, fourth and fifth reasons advanced under Issue 1.

Issue 3 - Whether claims 85 - 91 are patentable under 35 USC 103 over Bielinski in view of Brown?

The claims are patentable in view of the shortcomings in the cited combination of documents and the associated arguments that support their use that were detailed in issue 1. In particular, claims 85 - 91 are allowable for the first, second, third, fourth and fifth reasons advanced under Issue 1.

Issue 4 - Whether claims 92 - 96 are patentable under 35 USC 103 over Bielinski in view of Brown?

The claims are patentable in view of the shortcomings in the cited combination of documents and the associated arguments that support their use that were detailed in issue 1. In particular, claims 92 - 96 are allowable for the first, second, third, fourth and fifth reasons advanced under Issue 1.

Conclusion

For the extensive reasons advanced above, Appellant respectfully but forcefully contends that each claim is patentable. Therefore, reversal of all rejections is courteously solicited.

Respectfully submitted,

B.J. Bennett, President
Asset Reliance, Inc.
Dated: August 27, 2006

CLAIMS APPENDIX

69. A current operation modeling method, comprising:

integrating transaction data for a commercial enterprise in accordance with a common data dictionary;

using a neural network model to identify one or more value driver candidates for each of one or more elements of value from said data,

using an induction model to identify one or more value drivers from said candidates and define a contribution summary for each element of value for each of one or more aspects of a current operation financial performance using said value drivers, and

creating a plurality of network models that connect the elements of value to aspects of current operation financial performance using said contribution summaries

where the elements of value are selected from the group consisting of brands, customers, employees, intellectual capital, partners, vendors, vendor relationships and combinations thereof,

where the induction models are selected from the group consisting of lagrange, path analysis and entropy minimization,

where the network models support automated analysis through computational techniques and

where the aspects of current operation financial performance are selected from the group consisting of revenue, expense, capital change, cash flow, future value, value and combinations thereof.

70. The method of claim 69 wherein the method further comprises using a plurality of network models of aspects of current operation financial performance to complete analyses selected from the group consisting of identifying one or more changes to one or more elements of value that will optimize one or more aspects of enterprise financial performance, identifying a net value contribution of

each element of value, identifying a net impact of element of value changes on one or more aspects of enterprise financial performance, creating one or more usable forecasts without the use of a reconciliation system, identifying one or more transaction changes that will optimize one or more aspects of financial performance and combinations thereof.

71. The method of claim 70 wherein a Markov Chain Monte Carlo model is used to identify the changes that will optimize one aspect of enterprise financial performance, genetic algorithms are used to identify changes that will optimize one or more aspects of enterprise financial performance or multi-criteria optimization models are used to identify the changes that will optimize two or more aspects of enterprise financial performance.

73. The program storage device of claim 70 wherein the analyses are calculated for a specific point in time within a sequential series of points in time.

73. The method of claim 69 wherein a transaction is any event that is logged or recorded.

74. The method of claim 69 wherein each of a plurality of network models are causal network models.

75. The method of claim 74 where the causal network models identify a net contribution of each element of value to the value of each aspect of current operation financial performance over time where the net contribution of each element of value to each aspect of current operation financial performance further comprises the direct element contribution net of its impact on other elements of value.

76. The method of claim 69 wherein the data dictionary defines attributes selected from the group consisting of account numbers, components of value,

currencies, elements of value, units of measure, time periods and combinations thereof.

77. A program storage device readable by machine, tangibly embodying a program of instructions executable by a machine to perform method steps for performing a current operation method, the method steps comprising:

converting and integrating transaction data for a commercial enterprise by element of value in accordance with a common data dictionary;

using a sequence of analytical time series models to create a causal contribution summary for each of one or more elements of value for each of one or more aspects of current operation financial performance,

creating a plurality of network models that connect the elements of value to a value of each of one or more aspects of current operation financial performance over time using said contribution summaries,

completing analyses of one or more of the plurality of network models wherein the analyses are selected from the group consisting of identifying one or more changes to elements of value that will optimize one or more aspects of current operation financial performance, identifying a current operation value contribution of each element of value, identifying an impact of element of value changes on one or more aspects of current operation financial performance, creating one or more usable forecasts without the use of a reconciliation system, identifying one or more transaction changes that will optimize one or more aspects of financial performance and combinations thereof, and

displaying the results of the analyses

where the elements of value are selected from the group consisting of brands, customers, customer relationships, employees, employee relationships, intellectual capital, partners, vendors, vendor relationships and combinations thereof,

where the network models support automated analysis through computational techniques, and

where the aspects of current operation financial performance are selected from the group consisting of revenue, expense, capital change, cash flow, future value, value, raw material expense, manufacturing expense, service delivery expense, sales expense, support expense, other expense, change in cash, change in non-cash financial assets and combinations thereof.

78. The program storage device of claim 77 wherein the analyses are calculated for a specific point in time within a sequential series of points in time.

79. The program storage device of claim 77 wherein the sequence of analytical time series models further comprise a neural network model and an induction model.

80. The program storage device of claim 79 wherein a sequence of models complete analyses selected from the group consisting of a value driver candidate selection analysis, a value driver identification and contribution summary creation analysis, a causal component of value model development analysis and an element contribution percentage determination analysis and combinations thereof.

81. The program storage device of claim 77 wherein a contribution of an element of value to an aspect of current operation financial performance further comprises a total contribution of all value drivers associated with an element of value.

82. The program storage device of claim 81 wherein a value driver further comprises an item performance indicator selected for inclusion by an induction algorithm.

83. The program storage device of claim 77 wherein transaction data for a commercial enterprise are obtained from systems selected from the group

consisting of advanced financial systems, basic financial systems, operation management systems, sales management systems, human resource systems, accounts receivable systems, accounts payable systems, capital asset systems, inventory systems, invoicing systems, payroll systems, purchasing systems, the Internet and combinations thereof.

84. The program storage device of claim 77 wherein an element of value contribution summary further comprises a composite variable.

85. An optimization apparatus, comprising:

a plurality of enterprise transaction systems,

means for integrating and converting data from said systems in accordance with a common data dictionary by element of value,

means for analyzing at least a portion of said data to create a plurality of network models that identify a contribution for each of one or more elements of value to one or more aspects of current operation financial performance using said data,

means for using said models to identify one or more changes by element of value that will optimize one or more aspects of current operation financial performance, and

means for displaying the identified changes

where the aspects of financial performance are selected from the group consisting of revenue, expense, capital change, cash flow, future value, value and combinations thereof,

where the network models support automated analysis through computational techniques, and

where the elements of value are selected from the group consisting of brands, customers, employees, intellectual capital, partners, vendors, vendor relationships and combinations thereof.

86. The apparatus of claim 85 wherein enterprise transaction systems are selected from the group consisting of advanced financial systems, basic financial systems, operation management systems, sales management systems, human resource systems, accounts receivable systems, accounts payable systems, capital asset systems, inventory systems, invoicing systems, payroll systems, purchasing systems and combinations thereof.

87. The apparatus of claim 85 where the changes by element of value further comprise value driver changes.

88. The apparatus of claim 85 wherein one or more aspects of current operation financial performance are optimized for a specified point in time within a sequential series of points in time.

89. The apparatus of claim 85 wherein a Markov Chain Monte Carlo model is used to identify the changes that will optimize one aspect of current operation financial performance, genetic algorithms are used to identify changes that will optimize one or more aspects of current operation financial performance or multi-criteria optimization models are used to identify the changes that will optimize two or more aspects of current operation financial performance.

90. The apparatus of claim 85 wherein a contribution of each element of value to current operation financial performance further comprises a net contribution comprised of a direct element of value contribution to financial performance and one or more impacts on other elements of value.

91. The apparatus of claim 85 wherein analyzing the data to create a model of current operation financial performance further comprises creating a plurality of item performance indicators and completing analyses selected from the group consisting of a value driver candidate analysis, a value driver identification

analysis, a contribution summary development analysis and a component of value model development analysis.

92. A method for current operation optimization, comprising:

converting and integrating historical and forecast transaction data for a commercial enterprise in accordance with a common data dictionary,

using neural network models to identify one or more performance indicators for each of one or more elements of value,

identifying one or more value drivers from said indicators and defining a contribution summary for each element of value for each component of value using said value drivers,

creating a model of current operation financial performance by element and component of value using said contribution summaries, and

simulating a current operation financial performance using said model as required to identify changes by element of value that will optimize one or more aspects of current operation financial performance

where the elements of value are selected from the group consisting of brands, customers, employees, intellectual capital, partners, vendors, vendor relationships and combinations thereof, and

where the model of current operation financial performance supports automated analysis through computational techniques.

93. The method of claim 92 where the aspects of financial performance are selected from the group consisting of revenue, expense, capital change, cash flow, future value, value and combinations thereof.

94. The method of claim 92 where the contribution summaries further comprise value drivers and combinations of value drivers and where the contribution of each element of value to current operation financial performance further comprises a direct element contribution net of an impact on other elements of value.

95. The method of claim 92 where enterprise related transaction data are obtained from the group consisting of advanced financial systems, basic financial systems, operation management systems, sales management systems, human resource systems, accounts receivable systems, accounts payable systems, capital asset systems, inventory systems, invoicing systems, payroll systems, purchasing systems, the Internet and combinations thereof.

96. The method of claim 92 where the components of value are selected from the group consisting of revenue, expense, capital change and combinations thereof.

EVIDENCE APPENDIX

How to sort out the premium drivers of post-deal value

Bielinski, Daniel W. Mergers and Acquisitions. Philadelphia: Jul/Aug 1993.Vol.28, Iss. 1; pg. 33, 5 pgs

Subjects:	Valuation, Models, Cash flow forecasting, Acquisitions & mergers
Classification Codes	9190 US, 3100 Capital & debt management, 2330 Acquisitions & mergers
Locations:	US
Author(s):	Bielinski, Daniel W
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Abstract (Document Summary)

Value-based management (VBM) represents one of the latest advancements in discounted cash flow (DCF) modeling that is available to acquirers. VBM centers on what specific steps can be taken operationally and strategically to add value to a target after the deal is signed. It is based on the target's historical performance, rather than projections, and can show how the record might have been changed had managerial decisions and operating environments been different. Sensitivity analysis of past results offers clues to what can be done in the future and which value drivers should receive the most attention to achieve optimal rewards. The VBM technique allows the analyst to figure key decisionmaking trade-offs, since attention to one driver may generate negative effects on others or 2 or more drivers may have to be varied in concert to produce the best results.

Full Text (2640 words)

Many m&a professionals use a variety of computerized models to estimate the value of a company and guide them in setting purchase prices. However, relatively few buyers take advantage of the capabilities of these models to enhance their due diligence and formulate strategies for increasing the cash flow and enhancing the value of their acquired targets. Even fewer sellers use these models to help maximize the cash flows and values of their companies before putting their firms up for sale. Utilizing valuation tools solely to price companies is not unlike using a Ferrari to drive only to and from work -- a legitimate but limited use that ignores powerful potential. Indeed, as the art of modeling has progressed, new methodologies have been developed and applied to actual transactions in the ma market to sharply widen the utility and versatility of computer-based valuation approaches.

One particularly appealing advancement is Value-Based Management (VBM), which keys on a target's historical operations rather than future projections. VBM also can calculate the results of trade-offs when decisionmakers

must choose between a series of factors that can be changed to enhance postacquisition value.

Probably the best-known valuation tool designed to facilitate value creation and cash flow enhancement is Shareholder Value Analysis (SVA), introduced in the 1980s by Prof. Alfred Rappaport of Northwestern University. SVA may be defined as a two-step process. First, a discounted cash flow business valuation is performed. A projection of future cash flow (including a residual) is developed and discounted at an appropriate rate, usually the cost of capital, to arrive at an indicated value. Second, key factors (or value drivers), such as growth, profit margins, etc., are varied systematically to test the sensitivity of the indicated business value to each driver. Standard SVA sensitivity analysis changes each value driver plus or minus 1%, although analysts now often use "relevant ranges" and different percentages for upside and downside swings to reflect prevailing business realities.

SVA is a useful methodology, but, as with any tool, it has limitations. In working with middle-market companies, we have found that these limitations often are magnified into constraints that necessitate modifying standard SVA analysis. VBM, a first cousin to SVA, has resulted from these modifications and already has helped a number of middle-market companies improve their cash flows and values. The same techniques should prove useful to larger companies as well.

This article provides an abbreviated overview of VBM, describes how it differs from the traditional SVA framework, provides a simplified example, and discusses several applications in the m&a arena.

Although SVA has been in use for more than a decade, many executives still are leery of recommendations based on models that utilize projections, particularly when significant changes are suggested. Their argument is that when it's hard to predict results in the next quarter, how prudent is it to change a company's strategic direction based on a five-year projection?

Rather than use projections of future cash flow like SVA, the VBM framework utilizes historical cash flow. Five years of historical cash flow are added up to arrive at a cumulative baseline cash flow number. That is in contrast to SVA's method of discounting future cash flows to reach an indicated value.

Instead of testing the sensitivity of a value based on a projection, VBM tests the sensitivity of the historical cash flow. VBM tells the executive how much more or less cash flow would be in the bank today if certain events had occurred differently or if the company had operated differently in the past five years.

The use of actual historical data, rather than projections, has proven useful in testing the impact of alternative scenarios against the reality of actual events. It also has served as a catalyst to identify and implement actions that generate improvements. As long as a company's fundamental structure does not change going forward, the results provide meaningful insight regarding the probable outcomes of future strategic action. to the extent that risk is not increased, an executive may reasonably assume that an increase from historical cash flow trends likely would translate into enhanced value.

In the minds of some executives, particularly those with operations backgrounds, the traditional SVA "value drivers" are too far removed from daily operations to be relevant for short-term or medium-term planning. Therefore, VBM utilizes drivers that are more directly linked to operations. For example, rather than use operating profit margin as a broad value driver, a VBM analysis on a manufacturer would include a breakdown of cost of goods sold by key components. A probable mix would include:

* Materials -- The cost of raw materials and purchased components used in production, net of scrap sales.

* Human Resources -- All direct and indirect labor costs, fully loaded with all benefits -- regardless of where the accountants might classify them, i.e., in "General and Administrative" expense -- to get a true picture of manufacturing labor cost.

* Technology/Capital -- All costs associated with running and maintaining the manufacturing facilities and equipment (rent, depreciation, etc.) and R&D.

* Other Cost of Goods Sold -- Such as utilities, etc.

Compartmentalizing the costs allows managers to link strategy with pure day-to-day operating factors, such as

scrap rates, procurement procedures, pricing policies, etc. Much has been written about "linking" manufacturing operations to strategy as a means of establishing competitive advantage. VBM facilitates this process.

Traditional SVA assesses changes in one value driver at a time. But many strategic decision involve trade-offs, resulting in two or more value drivers changing simultaneously. The pressure on decisionmakers in those situations often is to concentrate change in the drivers that are assumed to offer the greatest enhancements in overall business value, even if such a focus in actuality works to the detriment of cash flow and value.

For example, a company might pursue lower-margin commodity business in order to grow by expanding the top line. Executives will be trading off profit margin for growth. But that's just for openers. A higher-growth game plan could necessitate increased capital expenditures -- to improve efficiency, increase production, or boost productivity -- so these additional costs must be incorporated in the decision. Since the net effect of such trade-of cannot be gleaned by simply "netting" the results of single-variable sensitivities, a model that can sort out concurrent changes in several value drivers can provide crucial information for an intelligent decision based on all relevant factors.

In the final analysis, VBM essentially utilizes SVA principles but advances the basic techniques by incorporating historical data, operations-linked value drivers, and concurrent changes in multiple value-drivers. So how does a VBM analysis look?

Table 1 shows a reconstructed historical operating cash flow statement for an actual company, using disguised data. (Table 1 omitted) As with traditional SVA, operating cash flows, which exclude interest expense and debt changes, are measured. Note the operations breakout -- showing that fully loaded labor is the largest single cost, materials is second, and other costs are relatively small contributors -- to determine the cost of goods sold. The ability to partition manufacturing costs in this manner is important to strategic decisionmaking. For example, while fully loaded human resources cost is about 33% of sales in Table 1. direct labor costs for the company were only 7%. This insight alone was an eye-opener for management.

The bottom-line operating cash flows for the five-year span are added up to produce a "total cumulative cash flow" of $1,174,000. This represents a baseline cash now number that can be used in conjunction with sensitivity analysis to determine exactly what factors really "drive" the company's cash flow ano value.

Table 2 shows the sensitivity of the baseline cash flow to changes in key factors. (Table 2 omitted) In other words, it demonstrates how the results might have turned out differently had operating or strategic changes been effected in the recent past. In turn, this suggests improvements that can be made in the tuture.

For example, a 5% annual increase in sales, while holding relative cost relationships constant, would have dramatically expanded cash flow by 84%. But such growth may be far more difficult to achieve than improving the productivity of operations. Thus, the sensitivity analysis also shows how changes in key cost and operating components can impact cash flow.

By comparing Tables 1 and 2, the analyst can determine which drivers can, if altered, impact cash flow the most. One striking conclusion is that the areas "where the big dollars are" do not always offer the greatest opportunities to improve cash flow and value. At our example company, Table 1 has established, human resources represent the largest component of cost of goods sold, suggesting that it is a labor-intensive operation.

working on fully loaded labor costs would not be unproductive. For a 1% cut, cumulative cash flow will expand by 7%. Moreover, the consequences of not controlling labor costs are dire, since the same 7-to-1 ratio works in reverse as a 10% rise in human resources costs chops cumulative cash flow by 70%. but the cash flow harvest is not as rich as in curbing material costs, where a 5% reduction will expand cumulative cash flow by 25%. Further, efforts to cut material costs often require less energy than a attack on labor costs, because many firms have tried to bleed every last dollar out of labor cost while ignoring material cost drivers like scrap and procurement.

With these data in hand, strategic changes now may be tied directly to manufacturing. Initiatives to control material costs, for example, might include standardizing or high unit cost/lower total cost through reduced scrap, eliminating overspecificallon on parts orders to vendors, and establishing better value chain management through closer relationships with suppliers. Reducing scrap or increasing growth may now be related directly to reducing setup times, streamlining the factory, shortening production runs, increasing manufacturing flexibility, and other factory-floor initiatives that impact costs, pricing, and competitive advantage.

Table 3 presents certain "bread-even trade-off," or how changes in two value drivers can offset each other and leave the baseline cash flow unchanged. (Table 3 omitted) Strategies can be evaluated in light of these trade-offs.

Complex modeling, varying three or more value drivers concurrently, is also possible. For example, our company in Table 1 may mount a strategy to enhance sales growth 5% a year by pursuing lower-margin business. Reaching the sales goal requires cutting gross margin 2%, stocking more product in inventory -- thereby reducing turnover by two turns -- and channeling an additional $50,000 a year into capital outlays. Unless there is an overwhelming competitive reason for a pure sales-growth strategy, the approach is self-defeating from a value standpoint. It would reduce historical cumulative cash flow by about 10%.

The Table 1 example utilized a manufacturer. While the value drivers used for, say, a distributor would be different, the same sorts of linkages to operations can he developed.

This framework offers multiple applications or corporate acquirers. Prior to an acquisition, the VBM model can help identify hidden potential for quick cash flow generation -- which is especially important for dealmakers in leveraged transactions. VBM has been used with great effectiveness in the due diligence process to evaluate risk. And postacquisition strategy formulation for the target also may include a VBM analysis.

Before making an acquisition, a company can derive great benefit from a VBM-based self-evaluation designed to identify strengths and weaknesses of its existing operations and strategies. It is a sad fact that many companies undertake acquisitions in an attempt to fix internal problems that they have not effectively addressed on their own. Invariably, they aggravate the problems by repeating the same mistakes on the targets they acquire and making both worse.

At a minimum, a VBM analysis night revel upside potential a buyer could "acquire into," or downside risk that could be diversified away through acquisition. For example, a company that faces hill downside risk if its growth slows might acquire a slow-growth, stable company to reduce the damage should the combined company not hit its growth targets

A related but much broader issue critical to both corporale acquirers and dealmakers involves the design of incentive compensation plans. Traditional incentive plans tend to be tired to accounting-based earnings measures that may not be the best gauges of value change. More recently, incentive plans tied to cash flow, the same basic yardstick used to measure value, have grown in popularity. However, there are two major difficulties in implementing a value-based incentive compensation plan -- it uses a projection that is generated by management, which means that it may be perceived by plan participants as self-serving, and there are problems in tying incentive plans to operations.

VBM addresses both of these concerns and offers the advantage of focusing on increments to value, rather than a single value for a company. The benefits of an incentive compensation plan for target management that is tied to value creation are compelling for the acquirer who is anxious to reap the greatest payoff from the combined organization.

On the other side, a potential seller can use VBM to "dress up" the business from a valuation standpoint before putting the company in play. Preferably, enhancement efforts should start three to five years prior to sale. This is especially important in the current m&a market where the seller gets paid more tor demonstrated results than for great potential.

Further. some potential sellers are looking to "get out from under" problems that seem unsolvable. VBM can be used to help get a handle on the company's performance and identify areas that can be improved under the present ownership. The exercise may lead the seller to conclude that the resulting cash flow and value benefits make the company worth keeping.

VBM also can be used to add credibility to a seller's projection of sales, earnings, and cash flows. A projection that has the same sensitivity profile as the historical performance enjoys greater believability. If projected cash flow improvements are similar in magnitude to improvements that could have been achieved historically, the forecast is more readily accepted by the buyer. And if both the acquirer and target utilize VBM in constructing a projection, the two sides might come close to reaching a consensus on what constitutes a "realistic" projection of future performance.

The valuation concepts and models that are so critical to effective pricing of companies enjoy much wider versatility than their most common uses. They can be sensibly employed to evaluate other key factors such as risk assessment and ongoing value creation that can make the difference between a success or a failure in an acquisition. They offer potential buyers and sellers powerful tools that might give them a competitive edge in the m&a arena.

KEYS TO CREATING VALUE

Value-Based Management (VBM) represents one of the latest advancements in Discounted Cash Flow (DCF) modelling that is available to acquirers. VBM centers on what specific steps can be taken operationally and strategically to add value to a target after the deal is signed. It is based on the target's historical performance, rather than projections, and can show how the record might have been changed had managerial decisions and operating environments been different.

Sensitivity analysis of past results offers clues to what can be done in the future and which value drives -- e.g., sales growth, profit margins, productivity, etc. -- should receive the most attention to achieve the optimal rewards.

Additionally, the VBM technique allows the analyst to figure key decisionmaking trade-offs, since attention to one driver may generate negative effects on others or two or more drivers may have to be varied in concert to produce the best results.

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He acknowledges the contribution to this article by Joseph R. Boehmer, a senior partner in Arthur Andersen's Enterprise Group in Milwaukee.

Neural Networks Enter the World of Management Accounting

Financial managers must keep up with this new realm of artificial intelligence, which is changing the way financial transactions are handled.

BY CAROL E. BROWN, CPA; JAMES COAKLEY; AND MARY ELLEN PHILLIPS, CPA

The next revolution is not coming—it is here! Just as the information highway has revolutionized the way we access, use, and store information, artificial intelligence (AI) is changing the way we practice accounting and structure internal controls.

Artificial intelligence is the study of how to make computers do things that people do better now. It has its roots in theorem proving, game playing, and general problem solving. As Figure 1 suggests, artificial intelligence is being used to address a wide range of areas that have resisted automation with conventional methodologies. These areas include formal tasks like mathematics and games; everyday, mundane tasks that most people do easily, like seeing, hearing, and using natural language; and tasks usually left to experts, like medical diagnosis and financial analysis.

AI is implemented in practice with a set of powerful tools and methodologies. Three of the most common methods parallel the way people reason: rules (inference procedures), cases (case-based reasoning), and pattern matching (neural networks). These methods may be used separately or in combination and currently are being used to solve a variety of business tasks.

JAY SILVERMAN/IMAGE BANK

GMAC approves credit for car loans with its neural network, Credit Advisor.

WHAT ARE EXPERT SYSTEMS?

When artificial intelligence techniques are applied to the area of expert problem solving, the result often is called an expert system. Rule-based procedures were the first to be applied successfully to solve problems previously done by experts. The term expert system was coined to refer to those systems. Early expert system definitions focused on rule-based methodologies.

Not all people use the term expert system in the same way. Some people still require that the systems be rule based, while others now include systems based on case-based reasoning and neural networks as well. Some people require expert systems to perform as well as the best experts, while others include systems that act as intelligent assistants. Some people require that expert systems use artificial intelligence techniques. Others use the term "expert system" for all systems that function in an expert domain whether they use artificial intelligence techniques or not. Explaining why something should not be considered artificial intelligence is easy; explaining why it should be is difficult.

The following trends are occurring

and will continue to occur:

- More businesses are learning about, experimenting with, and developing applications using artificial intelligence techniques to solve problems previously requiring human experts;
- Artificial intelligence techniques are being integrated with "traditional" data processing technology;
- Systems using artificial intelligence techniques are being targeted for the mass market in addition to applications developed for a specific company;
- Neural networks will enhance this growth.

Expert systems are used for tasks ranging from credit approval to preparation of comprehensive personal financial plans. Financial applications are the most frequent use of expert system technology. Expert system developers are welcomed into these markets where they are altering the financial services industry's competitive mix by fostering new services and instruments while supporting basic data processing.

Expertise Available. Expert system task domains require substantial specialized knowledge. For a rule-based system, the experts must communicate their expertise as rules. The expert's ability to select similar cases and to use analogy to solve cases is critical for case-based systems. For neural networks, the expert must select the facts and variables that are important to consider, and sufficient data must be available to train the network. Like human experts, expert systems make mistakes, so some percentage of incorrect or nonoptimal solutions should be acceptable if the technology is used.

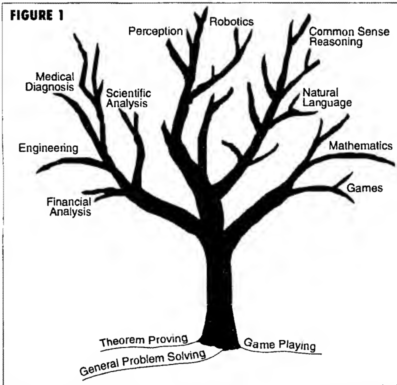
Matching the Technology with the Task. Rule-based technology is based on symbolic reasoning, so it works well for tasks based on applying rules, such as those in the tax and audit domains. Case-based systems reason by analogy, so they are effective for help desks. Neural networks use pattern matching. The financial services industry with its large databases has fielded several successful neural network applications, and neural networks based on information about customers or potential customers have proved effective. In fraud detection, they are integrated effectively into expert systems. If large databases exist with which to train a neural network, then use of that technology should be considered. For a neural network the large database can be used as the equivalent of the human expert. Each type of reasoning can be matched to tasks that require its specific reasoning strengths.

Experience with the Technology for the Task. Available information about current systems does not tell us which expert system tool to use to do a specific task. Most deployed systems are rule-based, but that fact does not suggest that rule-based technology is the most appropriate for all tasks—just that it has been in use the longest. As more applications employ a particular technology in a particular application area, using that technology becomes less risky.

Michael Hutson at General Motors Acceptance Corporation (GMAC) says management may be reluctant to deploy a system using newer, unproven technologies for tasks that are critical to the business. A simple rule is: An unproven technology requires more management commitment. Developers should focus on either creating a system using known technology or advancing technology but not both simultaneously. For example, in 1987, after less than two years of development, GMAC deployed its first credit system using established rule-based technology. That same year, GMAC began to experiment with neural networks. But the neural networks were not deployed until 1992. In the end, the neural network technology was successful for GMAC, but the development time and the lag before deployment were much longer than for the more established rule-based technology. Addressing all management's concerns about neural network technology, including the legal ramifications, took almost two years.

Importance of Explanation. The lack of causal explanation in neural networks makes some developers reluctant to use it. For example, Park City Group, the developer of PaperLess Management, a set of 25 expert systems for managing a multilocation retail business, has experimented with neural networks but has chosen not to use them for this reason. Another developer, Stottler, Henke Associates, Inc., considered all three technologies for its sales forecasting system, Retail Sales Prediction. It rejected rule-based reasoning because of the complexity of the rules required and neural network technology because of the need to explain the predictions to store managers. The firm chose case-based reasoning because it provided good

FIGURE 1



Developed from material in Elaine Rich and Kevin Knight, *Artificial Intelligence*, 2nd ed., McGraw-Hill, New York, N.Y., 1991. Copyright Carol Brown (1993). Used with permission.

predictions with little development effort and a way of explaining the prediction to the store managers.

Learning. Human experts automatically adapt to changing environments, but rule-based expert systems must be updated explicitly. This lack of ability to adapt to change automatically is one of the drawbacks of rule-based systems. Case-based reasoning systems can update the case base automatically, and neural networks can be retrained automatically as new data become available. For tasks requiring frequent updates of data, case-based reasoning and neural networks have a significant advantage over rule-based systems.

NEURAL NETWORK SYSTEMS IN USE

Many credit approval expert systems employ neural network technology. Neural networks also are used to determine compliance with a bank's policies and to detect fraudulent transactions in an arena where traders make millions of dollars of trading decisions daily. Neural networks are good tools for fraud detection because of the volume of data available to create the network and the need to discover unusual or abnormal transactions. All these areas have large accessible databases of case information.

There are many other financial applications that also use neural networks. The systems usually are not discussed in the literature because of their proprietary nature. When they *are* discussed, the type of expert system may not be easily discernible. Here we will show you seven examples of neural networks that companies are using today.

FORECASTING AND SCHEDULING

Neural networks are used for forecasting future sales and prices, estimating future costs, and planning future schedules and expenditures. Airlines must schedule use of their airport gates, which changes constantly because of flight takeoff delays and late-arriving flights.

Air Canada's neural network, developed using the Symbolic Spreadsheet by Texas Instruments, does its airport gate scheduling. The improved scheduling makes aircraft operations more predictable, reduces delays, and reduces fuel costs by shortening the time aircraft spend waiting for available gates. More efficient scheduling raises the number of flights by each aircraft, increases revenue, provides better management of disruptions, and improves passenger service. Air Canada anticipates expanding its system to manage adjacent ground resources such as aircraft cleaning crews, commissary, and baggage handling.

Some companies are using neural networks to find qualified customers. Churchill Systems, a provider of hospital supplies, uses a neural network to identify the key characteristics of the best customers and searches the inactive customer list for the highest probability purchasers from those who are inactive.

Neural networks also help with customer service and support. As businesses reorganize based on customer needs, neural networks can help them analyze past business transactions so they can understand their customers' buying patterns. HNC Software Inc.'s neural network for database mining has been tailored for database marketing by Custom Insight Co. Bank-tec has a neural network that reads and approves the handwritten numerals on the face of each check. The system saves the bank thousands of dollars each year.

Courtesy of HNC, Inc

MONITORING TRANSACTIONS FOR FRAUD

Monitoring transactions to detect fraud is an important application area. Both neural networks and rule-based systems are used for screening large numbers of similar transactions for fraud. This ability to screen all transactions is especially important in fraud prevention. Industries with large-scale fraud problems, like the credit card industry and the health insurance industry, are particularly active in developing neural networks.

The credit card industry is especially vulnerable to fraud from credit cards lost by or stolen from the card holder, cards intercepted before they reach their intended users, and counterfeit cards. Neural networks have been effective in preventing the use of these credit cards by criminals.

FALCON by HNC, Inc., is a credit card fraud prevention system used by six of the 10 largest credit card companies. Users include First Chicago; Household Credit Services, Inc.; AT&T Universal Card Services; and Visa U.S.A. The system uses primarily neural network-based technology and has some database, rule-based, and statistical modeling capabilities. It creates an individual behavior file for each account using pools of fraud data. FALCON detects patterns that may be fraudulent as it examines each transaction. When FALCON decides that fraud is likely, it provides strategies for follow-up. FALCON has been saving clients from 20% to 50% more than their existing fraud detection systems. Colonial National Bank reported that FALCON reduced losses due to nonreceipt of cards and counterfeiting by as much as 50%. The processing of merchant sales drafts and payments, however, continues to resist efforts at complete automation. HNC is looking at debit card fraud, merchant fraud, and health insurance fraud for more applications.

A few years ago a large bank experienced several million dollars in credit card losses and needed a system to fight this credit card crime. Fraud Detection System, developed by Nestor, Inc., for the bank is a mainframe-based neural network designed to control losses from credit card transactions. The system calculates the likelihood that a current transaction is fraudulent based on the card's history and various models of criminal behavior. The bank uses the system's information to notify VISA and Mastercard to either accept or deny a transaction or to request more information from the card holder. (Nestor now has introduced PRISM, for proactive fraud risk management, which operates corss-platform on mainframes, UNIX workstations, or networked PCs.)

Chase Manhattan Bank, GE Capital, and Colonial National Bank also have neural networks to fight credit card crime. Their systems sift through hundreds of thousands of credit card transactions daily and flag possible fraudulent ones. In tests run by GE Capital, its neural network detected 40% of fraudulent transactions with only a 1% false positive.

STUART DEE/IMAGE BANK

Neural networks can predict the performance of stocks and bonds to help traders make their buy, hold, and sell decisions.

FOREIGN CURRENCY TRANSACTIONS

One fraudulent transaction in foreign currency trading can cause millions of dollars in losses for a bank. One type of fraud is a trader colluding with a customer and splitting the profits. Chemical Bank needed a practical, cost-effective, and powerful solution to monitoring a high-volume, high-risk business given a severe scarcity of expertise available in detecting this type of fraud.

Chemical Bank's Inspector is a neural network with some rule-based technology that monitors (audits) high-volume, high-risk foreign currency trading. It was developed using Nexpert Object by Neuron Data and ART-IM by Inference Corp. Each day the system reviews thousands of transactions around the clock and around the world that represent more than $1 billion in trades. The system produces a management alert report summarizing any unusual findings. Then a foreign exchange manager reviews the flagged trades. The flags earmarking a fraudulent transaction are dollar volume for that type of trade, historical norms, and other trading pattern disruptions.

For proprietary reasons, the bank will not reveal the success of the system. If Inspector identifies one fraudulent transaction, however, it would pay for itself several times over. The bank's management believes the system is a powerful deterrent to fraud. Chemical Bank's traders worldwide know all transactions are reviewed by management daily—a powerful defensive weapon. The bank's management believes the system provides a level of control and information not available previously.

INVESTMENTS

Many systems also have been developed to help investors and investment companies manage investments in securities. Fidelity has a neural network it uses as a decision aid in stock purchases for mutual funds. The neural network makes a very accurate forecast about 10% of the time; the other 90% of the time it makes no forecast at all.

Deere & Co. uses a neural network to manage the $100 million equity portfolio of its pension fund. Forty indicators are used to rank the expected future returns of 1,000 equities. Currently owned stocks are sold and are replaced by those with future return rating over a certain cutoff, which results in an 80% monthly turnover. The portfolio return, net of transaction costs, exceeds that of the Standard & Poor's 500 index.

John W. Loofbourrow Associates, Inc., uses a PC-based neural network to predict the S & P 500 index. Shearson Lehman's neural network predicts the performance of stocks and bonds to help market traders in making their buy, hold, and sell decisions. The system recognizes patterns in market activity before they are apparent to a human, which may mean millions in trading profits. A program called Braincel from Promised Land Technologies, Inc., has been used successfully for trading 30-year Treasury bond futures. Braincel is a neural net add-in to Excel for MS Windows. According to company owner, Stanley Dalnekoff, at the moment it is used mainly by financial forecasters trying to make their fortunes—with varying degrees of success. Dalnekoff is a Scottish Chartered Accountant and is interested in using Braincel for other financial and accounting purposes.

CREDIT GRANTING

Neural networks are valuable for credit granting. "Recent experiments testing the consistency and quality of individual loan officers' credit assessment skills show dramatic gaps and inconsistencies. Individual officers change their risk grades over time. Collectively, bank lenders fail to meet their institutions' defined acceptable standards by wide margins, especially for riskier loans."[1]

Citibank uses a neural network to process credit card applications. The system can process an application in one to five minutes instead of the previous several-day process.

American Express's *Knowledge Highway* is used for processing credit card applications, processing transactions, and collecting overdue accounts. The system is considered a very ambitious effort in expert system use. American Express is building a "knowledge highway" in which intelligent computers will help people with every step of the job of managing credit. The system has neural networks to evaluate credit risks via credit scoring. For overdue accounts, the computer assembles the information needed to analyze an account, reviews applicable state and national laws, generates the collection letter, files all the paperwork, and creates a reminder for the collector. The system changed the hiring from number crunchers to employ-

ees with high people skills and broadened the scope of the positions.

General Motors Acceptance Corporation (GMAC) approves credit for automobile loans with its two neural-network Credit Advisor systems. Credit Advisor is integrated into a mainframe-based consumer credit scoring application program. The neural networks evaluate credit for customers who are leasing automobiles and for customers who are buying them.

These systems fine-tune the existing credit-granting process. Management believes the ideal system should approve at least 20% of the credit applications. Before the neural networks were developed, fewer than 20% were approved. With the neural networks, 30% receive automatic approval.

About 800 car dealers use *Credit Advisor* to make credit decisions. GMAC has not performed a cost/benefit analysis yet because the system has not been in operation long enough for the company to learn if the credit approvals made by the system were good choices. The company *has* experienced savings in person hours for making credit decisions, reduced training costs, and fewer write-offs. Standardizing the credit-granting process also has reduced the effort of GMAC's internal audit staff.

Chase Manhattan Bank uses its neural network to evaluate commercial loan applications for its $300 million annual loan business. The neural network reduces loan losses by helping assess the credit worthiness of potential borrowers. The system identifies the strengths and vulnerabilities of the borrower and forecasts the impact of those factors for three years.

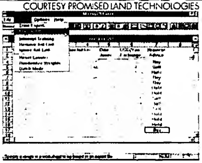
PROPERTY VALUATION

HNC, Inc.'s neural network, AREAS, is a residential property valuation system. AREAS automatically provides a baseline appraisal value and explains the factors that contribute to or detract from the property value. The system includes a continuously updated database of recent sales and other data. Valuations are based on the location and physical characteristics in relation to other comparable properties.

COST ENGINEERING

A neural network that would estimate the cost of pumps using flow and head parameters was developed to demonstrate the application of neural networks to cost engineering. The author, Robert McKim, compared the results of three other methods of estimation to the neural network and concluded, "Neural networks appear to have great potential in the estimation of non-deterministic costing systems ...[and] the potential to eventually be regarded as suitable and as practical as spreadsheets are today for cost engineers."

COURTESY PROMISED LAND TECHNOLOGIES



Braincel screen.

ENSURING EMPLOYABILITY

As we have shown, neural networks are being used for a variety of financial management applications from detecting fraud to granting credit to estimating costs to planning future schedules to determining compliance with a bank's policies. But all these areas require users to have developed good technology skills. Becoming experienced as a developer and applier of new technology such as neural networks is the best way for you as a management accountant/financial manager to ensure long-run employability. If you fight technological change, the best possible outcome is only a temporary reprieve. ■

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4. Neuron Data, 156 University Avenue, Palo Alto, CA 94301, (415) 321-4488.
5. NeuralWare Inc., Penn Center West, Bldg. 4, Suite 227, Pittsburgh, PA 15276, (412) 787-8222, Fax (412) 787-8220.
6. Promised Land Technologies, Stanley Dalnekoff, 195 Church Street, New Haven, CT 06510, (800) 243-1806.

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Note:
The published sources of information for this article are far too numerous to list here. Additional information and specific source references for most of the systems discussed can be found in: C.E. Brown and M.E. Phillips, Expert Systems for Management Accounting Tasks, *Institute of Management Accountants, Montvale, N.J., 1995.*

[1] M.E. Blake, III, "Rethinking the Corporate Credit Process," *The Bankers Magazine*, Vol. 175, No. 1, 1992, p. 31.

CREATING SHAREHOLDER VALUE

A GUIDE FOR MANAGERS AND INVESTORS

REVISED AND UPDATED

ALFRED RAPPAPORT

*f*P

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Cost of equity = Risk-free rate + Equity risk premium

Even government securities are not entirely risk-free. While they are essentially free of default risk, they are not free from increases in interest rates and the resulting capital losses. For an investor with a long-term horizon, even short-term Treasury bills carry interest rate risk because yields will fluctuate over time. In the absence of a truly riskless security, the rate on long-term Treasury bonds serves as the best estimate of the risk-free rate. Just as in the case of estimating the cost of debt earlier, the time horizon for estimating the cost of equity should be consistent with the long-term horizon of the cash flow forecast period. The use of long-term Treasury bond rates accomplishes this purpose and in addition captures the premium for expected inflation. After all, the rate of return demanded by investors includes not only the "real" interest rate (compensation for simply making the investment), but also compensation for expected inflation:

Risk-free rate = "Real" interest rate + Expected inflation rate

The second component of the cost of equity is the equity risk premium. One way of estimating the risk premium for a particular stock is by computing the product of the *market* risk premium for equity (the excess of the expected rate of return on a representative market index such as the Standard & Poor's 500 stock index over the risk-free rate) and the individual security's systematic risk, as measured by its beta coefficient.[5]

Risk premium = Beta (Expected return on Market – Risk-free rate)

The market risk premium represents the additional compensation that investors expect for holding stocks rather than "risk-free" government bonds. The premium should be based on expected rates of return rather than average historical rates. This approach is crucial because with the increased volatility of interest rates over the past two decades the relative risk of bonds has increased, thereby lowering risk premiums to a range from 3 to 5 percent. Those who estimate the market risk premium as the long-run average excess of stock returns over government bond returns will typically obtain a figure in the 7 to 9 percent range. This historical approach ignores that market risk premiums vary over time and at the present time can lead to significant undervaluation.

To estimate expected rate of return, analysts' projections for earnings and payout ratios are combined to generate near-term as well as long-term dividend forecasts. The discount rate that equates the forecasted dividend stream to the current stock price is the implied or expected

time producing only average market returns for shareholders, they sometimes jump to two mistaken and dangerous conclusions:

1. The market does not actually value the long-term productivity of the company but judges it by its short-term performance.
2. Management must depart from the shareholder-value model to improve its company's competitive position.

Surveys invariably show that CEOs do not believe that the market fairly values their company's shares. A month before the market crashed in October 1987, Louis Harris and Associates conducted a poll of one thousand CEOs. The pollsters asked: "Is the current price of your company's stock an accurate indicator of its value?" Of the 58 percent who responded "no," virtually all believed the market was undervaluing their shares. More recent surveys report similar findings. Why do CEOs persist in the belief that their company's shares are not fairly valued? One possibility is that managers know more about their businesses than the market does and thus arrive at a different, often higher, value for their company's shares. But, even when a company liberally discloses information, the market may still arrive at a value different from management's. Another possibility is that CEOs simply tend to respond more optimistically to surveys.

While the reasons for the market versus management valuation disparity may be ambiguous, its consequences are not. The disparity has caused many managers to persist in the mistaken belief that the market relies on short-term earnings rather than a long-term valuation of cash flows. In turn, this preoccupation with the short-term has caused too many managers to sacrifice crucial investments with substantial long-term payoffs in order to report better short-term earnings. This short-term view is not only competitively debilitating but it also is based on an inaccurate view of the market's pricing mechanism.

There are three factors that determine stock prices: cash flows, a long-term forecast of these cash flows, and the cost of capital or discount rate that reflects the relative riskiness of a company's cash flows. The present value of a company's future cash flows, not its quarterly earnings, determines its stock price. Fortunately, there is considerable evidence that the stock market takes the long view.

The most direct evidence comes from assessing what the stock price tells us about the market's expectations concerning the company's future performance. In other words, what level and duration of cash flows justify today's stock price? Studies consistently confirm that current stock prices are based on long-term forecasts of cash flows. For example, The

Value Driver Assessment

A value audit enables managers to monitor overall value creation. However, this is not the level that day-to-day decisions are made in operating units. Hundreds of factors influence the value of any business and, faced with the task of managing them, many executives find it difficult to set priorities. One of the most important contributions of shareholder value analysis is that it enables operating managers to determine which activities in their business must be managed most actively.

Business value depends on the seven financial value drivers that have been emphasized throughout this book: sales growth, operating profit margin, incremental fixed capital investment, incremental working capital investment, cash tax rate, cost of capital, and value growth duration. While these drivers are critical in determining the value of any business, they are too broad to be useful for many operating decisions. To be useful, operating managers must establish for each business the micro value drivers that influence the seven financial or macro value drivers. Figure 9–3 presents an example of the linkage between micro and macro value drivers.

An assessment of these micro value drivers at the business unit level allows management to focus on those activities that maximize value and to eliminate costly investment of resources in activities that provide marginal or no potential for creating value. Value driver analysis is a critical step in the search for strategic initiatives with the highest value-creation leverage. Isolating these key micro value drivers enables management to target business unit operations that have the most significant value impact and those most easily controlled by management. This analysis also produces the "leading indicators of value" discussed in Chapter 7. A business unit value driver analysis is accomplished in three steps.

The first step is to develop a value driver "map" of the business. This involves identifying the micro value drivers that impact sales growth, operating profit margins, and investment requirements. Figure 9–4 presents a value driver map for the retailing operating costs of a petroleum marketing business. The company began by separating operating costs into seven categories. These categories were then further divided into their respective key value drivers.

Armed with a better understanding of micro value driver relationships, the next step is to identify the drivers that have the greatest impact on value. To establish the sensitivity of value to a particular value driver, the relevant range for that driver must first be estimated. The relevant

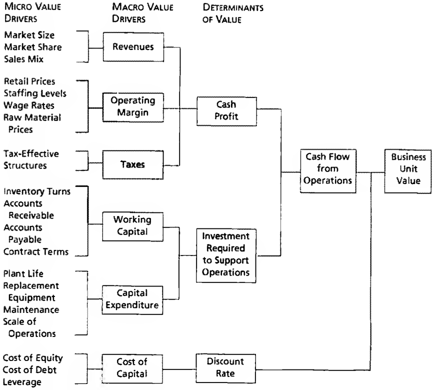

Figure 9–3. Micro and Macro Value Drivers

range can be estimated by considering historical performance, target performance, and performance benchmarked against leading competitors. Figure 9–5 presents the sensitivity of shareholder value to changes in selected drivers for retail as well as industrial marketing. For simplification purposes each driver varies by 10 percent except for discounts to industrial customers, which are tested for a 1 percent variation.

Most managers believe they can identify the key drivers for their business. However, these drivers may in many cases be appropriate for a short-term-earnings-driven business rather than an organization searching for long-term value. Experience shows that value driver sensitivities are not always obvious. Therefore, quantifying sensitivities is a valuable exercise for both operating and senior management. For example, the petroleum marketing business historically has focused on increasing volume to industrial customers and carefully managing trucking costs. Surprisingly, as Figure 9–5 shows, trucking costs have a relatively minor impact on value.

The third step in the assessment of value drivers is to isolate drivers